Impact of Input Data Preparation on Multi-Criteria Decision Analysis Results

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Abstract. Multi-criteria decision analysis (MCDA) methods support stakeholders in solving decision-making problems in an environment that simultaneously considers multiple criteria whose objectives are often conflicting. These methods allow the application of numerical weights representing the relevance of criteria and, based on the provided decision matrices with performances of alternatives, calculate their scores based on which rankings are created. MCDA methods differ in their algorithms and can calculate the scores of alternatives given constructed reference solutions or focus on finding compromise solutions. An essential initial step in many MCDA methods is the normalization procedure of the input decision matrix, which can be performed using various techniques. The possibility of using different normalization techniques implies getting different results. Also, the imprecision of the data provided by decision-makers can affect the results of MCDA procedures. This paper investigates the effect of normalizations other than the default on the variability of the results of three MCDA methods: Additive Ratio Assessment (ARAS), Combined Compromise Solution (CoCoSo), and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The research demonstrated that the normalization type's impact is noticeable and differs depending on the explored MCDA method. The results of the investigation highlight the importance of benchmarking different methods and techniques in order to select the method that gives solutions most robust to the application of different computing methods supporting MCDA procedures and input data imprecision.

Keywords: Multi-criteria decision analysis · MCDA · Normalization · Input data preparation.

1 Introduction

Multi-criteria decision analysis (MCDA) methods support decision-making processes for problems that require simultaneous consideration of multiple conflicting criteria. Currently, many MCDA methods are available that differ in their

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algorithms, which scale the input data differently and determine the best solution. Differences in MCDA methods obviously produce different results, which can cause confusion among stakeholders [6]. The importance of this problem is evidenced by the fact that published studies of the impact of normalization techniques on the results of MCDA methods can be found in the literature. For example, Jafaryeganeh et al. studied the impact of four normalization methods (linear, vector, minimum-maximum, and logarithmic) for the WSM, TOPSIS, and ELECTRE methods for a case study of ship internal layout design selection [7]. Vafaei et al. studied the effect of Max, Min-Max, Sum, and Vector on the MCDA Simple Additive Weighting results for the supplier selection case study [12, 13]. As can be noted, there have been several attempts to formulate methods for evaluating the most appropriate normalization techniques for decision-making problems, which indicate obtaining different MCDA results depending on the chosen normalization techniques [15]. However, they are characterized by a lack of consistency and a robust evaluation framework that takes into account aspects such as the repeatability of the test, the universality of the problem domain, and the impact of the structure of decision problems in the form of different dimensions of the matrix representing the problem.

The initial stage of most MCDA methods is a normalization of a decision matrix containing performance values of considered alternatives regarding criteria assessment [1]. Normalization of the decision matrix plays a significant role in MCDA methods [16]. With this procedure, it is possible to use data provided in different units and for criteria with different objectives without requiring additional action regarding preprocessing data by the decision maker [3]. There are many normalization techniques, and among the most popular used in MCDA procedures are minimum-maximum, sum, maximum, vector, and linear normalizations [4]. The original algorithms of many MCDA methods have normalization methods assigned to them by their authors. For example, vector normalization is recommended for Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), minimum-maximum normalization is advised for Multi-Attributive Border Approximation area Comparison (MABAC) [8] and Combined Compromise Solution (CoCoSo) [17], linear normalization is one of the stages of Weighted Aggregated Sum Product Assessment (WASPAS) [11] and COmbinative Distance-based ASsessment (CODAS) [14], sum normalization is recommended for Additive Ratio Assessment (ARAS) [5]. Normalization techniques must also be suited for a given decision-making problem. Not every type of normalization can be applied to data containing negative or zero values due to the nature of the mathematical operations required [1]. In such cases, the original normalization technique for a given method must be replaced by another. For instance, minimum-maximum normalization is adequate for data including negative and zero values. However, such a procedure can lead to variability in the results. Variability of values in the decision matrix may occur not only due to different normalization methods but also when decision-makers provide imprecise data, which can also affect the results.

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In this paper, the authors present a benchmarking procedure as a numerical experiment that makes it possible to evaluate selected MCDA methods concerning their robustness to changes in values in the decision matrix caused by applying different normalization methods. In addition, the numerical experiment makes it possible to identify the normalization methods that, for a given MCDA method, cause the greatest and least variability in rankings compared to the original normalization. The procedure presented can be useful when it is necessary to choose a different normalization technique than the original one due to the data. Besides, the procedure can facilitate the identification of the MCDA method that is most resistant to data variability in the case of awareness of input data imprecision.

2 Methodology

Three MCDA methods were selected for this research, including TOPSIS [9], ARAS [5], and CoCoSo [17]. All three methods use a different normalization of the decision matrix in the initial step. In evaluating alternatives, the ARAS method determines the utility of each considered option relative to the ideal solution, which effectively supports the prioritization of alternatives. In the original algorithm of this method, the decision matrix is normalized using sum normalization [5]. The TOPSIS method is also based on reference solutions, except that it evaluates alternatives concerning their distance from the ideal and anti-ideal solution using the Euclidean distance metric. In the original version of the TOPSIS algorithm, vector normalization is used to normalize the decision matrix [9]. The CoCoSo method also uses normalization of the decision matrix, but it evaluates alternatives differently from the TOPSIS and ARAS methods. CoCoSo considers a combination of compromise approaches. Its algorithm includes an integrated simple additive weighting and exponentially weighted product model and can provide comprehensive compromise solutions [17].

Since the main focus of this paper is decision matrix normalization techniques, the basics and mathematical formulas of the particular normalization methods investigated in this paper are presented below. The fundamentals and formulas of the MCDA methods investigated are provided in Supplementary material in an open-source repository made available by authors on GitHub [2]. The Supplementary material also explains normalization methods applied in this research, namely minimum-maximum, maximum, sum, linear, and vector, together with mathematical formulas describing them. The research was conducted using a Python 3 script implemented in the Visual Studio Code environment based on the pseudocode provided in Listing 1 using MCDA methods and supporting techniques from the author's pyrepo-mcda Python 3 library [16]. GitHub also provides software in Python 3 implemented for procedures performed in this paper.

Numerical Experiment. Listing 1 demonstrates a research algorithm in the form of pseudocode employed for the numerical experiment performed in this paper. The experiment was conducted for each considered MCDA method:

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ARAS, CoCoSo, and TOPSIS in an iterative procedure involving 1000 iterations. The convergence of the rankings obtained using the original normalization for the given method with the rankings received using the four alternative normalization techniques was examined.

Algorithm 1 Research algorithm for benchmarking normalization methods.

```
iterations ← 1000
list_of_matrix_sizes ← matrix_sizes
for i = 1 to iterations do
    for s in list_of_matrix_sizes do
        matrix ← generate_random_matrix(s, s)
        types ← determined_criteria_types
        weights ← generate_weights(matrix)
        rank_ref ← mcda_method(matrix, weights, types, default_normalization)
        normalizations ← list_of_normalizations
        result ← empty_list()
        for normalization in normalizations do
            rank ← mcda_method(matrix, weights, types, normalization)
            result.append(correlation(rank_ref, rank))
        end for
        save_result(result)
    end for
end for
```

The convergence of rankings was determined using two rank correlation coefficients: the Weighted Spearman rank correlation coefficient r_w [9] and the Spearman rank correlation coefficient r_s [10]. The procedure was repeated for different dimensions of decision matrices $\{5\times5, 8\times8, 11\times11, 14\times14, 17\times17, 20\times20\}$ filled with random values in the range from 1 to 100. The criteria weights were determined by the CRITIC (Criteria Importance Through Inter-criteria Correlation) method [11]. Types of all criteria were set as profit.

3 Results

This section presents the results of numerical experiments investigating the effect of using alternative normalization techniques on the outcomes of three MCDA methods: ARAS, CoCoSo, and TOPSIS. The correlation results of the compared rankings are shown in the graphs in Fig. 1 for the ARAS method, Fig. 2 for the CoCoSo method, and Fig. 3 for the TOPSIS method.

Fig. 1 shows the results of comparisons of ARAS rankings obtained using sum normalization as in its original algorithm with the results obtained with linear, maximum (Max), minimum-maximum (Minmax), and vector normalizations. It can be observed that for the matrix dimensions examined, the results obtained using vector normalization converge most closely with sum normalization. In

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contrast, the lowest values of convergence were obtained for minimum-maximum normalization. The values of both correlation coefficients are high and, in most cases, range from 0.8 to 1. It implies that the ARAS method shows high resilience to changes in the value of the decision matrix caused, for example, by the normalization technique chosen for data preprocessing. The correlation values are also high when the dimensions of the decision matrices are increased, which means that an increase in the complexity of the decision problem does not reduce the convergence of the obtained results.

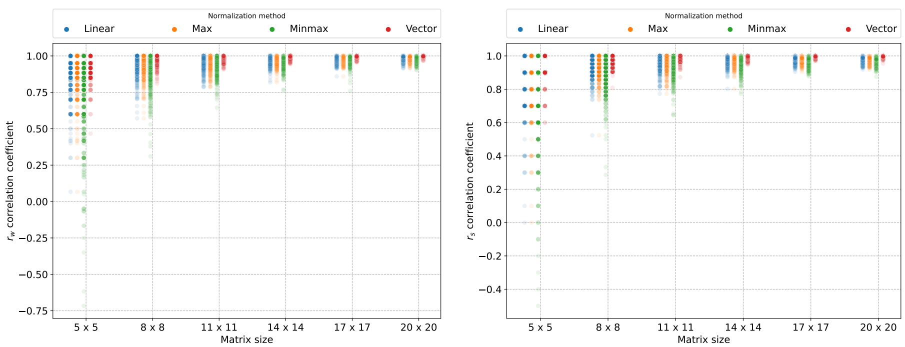

Fig. 1. Comparison of sum normalization results with alternative normalizations for ARAS.

Fig. 2 shows the results of comparisons of CoCoSo rankings obtained using minimum-maximum normalization as recommended in the original algorithm, with the results obtained using linear, maximum, sum, and vector normalizations.

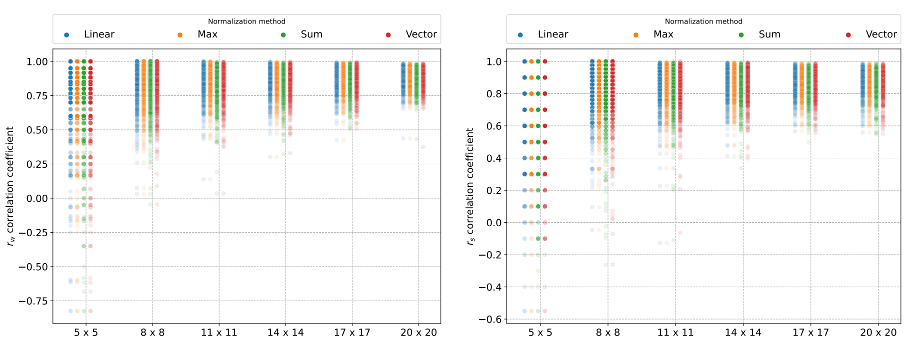

Fig. 2. Comparison of minimum-maximum normalization results with alternative normalizations for CoCoSo.

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In this case, the correlation values for the compared rankings are lower than for the experiment conducted for the ARAS method. It indicates that the CoCoSo method is more sensitive to changes in the input data caused by other normalization methods, resulting in noticeable changes in the results. For CoCoSo, the level of divergence of the compared rankings is comparable to the alternative normalizations included in the experiment.

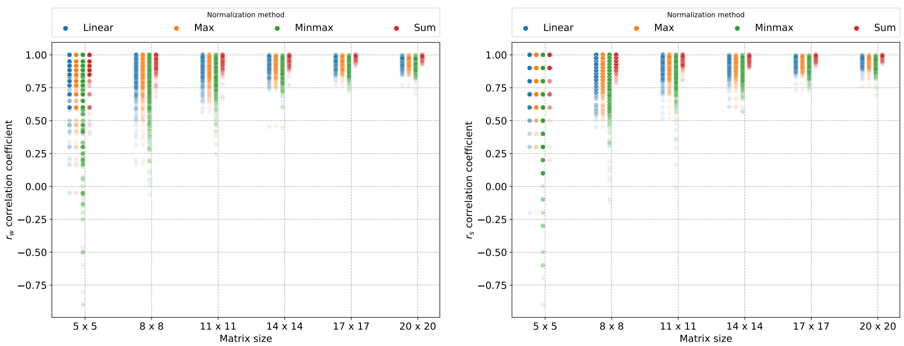

Fig. 3. Comparison of vector normalization results with alternative normalizations for TOPSIS.

Fig. 3 displays the results of the experiment conducted with the TOPSIS method. In this case, rankings obtained using the vector normalization suggested in the original TOPSIS algorithm were compared with those obtained using alternative normalizations. The received correlation values for the compared rankings are similar to the experiment for the ARAS method, but the values of the r_w and r_s coefficients are slightly lower. As for the ARAS method, the highest correlation values were registered for rankings generated using sum and vector normalizations. On the other hand, the lowest correlations occurred for rankings obtained using minimum-maximum and vector normalizations.

4 Conclusions

The multitude of MCDA methods and supporting techniques cause decision makers to often wonder which method will be most suitable for solving considered decision problems. These doubts are justified because applying different computing techniques affects the results obtained differently. This influence is evident from the initial stages of MCDA methods, including providing performance data by decision-makers and data normalization. Therefore, an important role in MCDA procedures is played by benchmarking, demonstrating the impact of different methods on the variability of results. The research presented in this paper showed that the use of different normalization techniques causes variability in the MCDA results obtained, which differs depending on the normalization

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technique and MCDA method. The main implication of the presented research is a universal framework that enables experiments to test the impact of different normalization techniques applied to different MCDA methods and different complexity of data structure using two objective correlation metrics. Such a framework can be applied to analogous studies with different parameters depending on the objectives of the researchers. An experiment considering ARAS, CoCoSo, and TOPSIS showed that the ARAS method was the most resilient to changes caused by different normalization techniques, giving the most convergent rankings using sum and vector normalization. On the other hand, CoCoSo showed the least resistance to normalization change. The comparable results for ARAS and TOPSIS are due to the similar algorithms considering the reference solution.

This research has some limitations, among which are the inclusion of only three selected MCDA methods and five normalization techniques. Thus, future work directions include exploring the effect of the applied normalization on the results of other MCDA methods using normalization, such as MABAC, WASPAS, CODAS, COPRAS, MOORA, and MULTIMOORA and consideration of other normalization methods.

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